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Polarization and Persistence
in the Japanese Labor Market *

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Abstract

This study analyzes the persistence of regular and non-regular employment status in Japan for workers that change jobs. In particular, we investigate two hypotheses behind this persistence. The first is the dependence of the employment status in the current job on that in the previous job. The second is the dependence of the employment status in the current job on that in the initial job, which is called first job effects. While both types of dependence are empirically verified, the former is shown to be quantitatively more substantial. Therefore, the serially dependent structure of employment status matters critically to the segmentation of the labor market in Japan.

JEL Classification: J42, J62, J70, C35.

Keywords: dual labor market, non-regular workers, state dependence, cohort effects, first job effects, Japanese labor market.

1 Introduction

The sharp increase in the number of non-regular workers has become a major issue in Japan. The concept of non-regular employment is generally used to denote the opposite of regular employment, which refers to stable, long-term, and full-time jobs. Because non-regular workers receive limited opportunities for on-the-job training and career development, increasing the relative share of such workers has been considered to represent a collapse of the traditional Japanese employment system.[1] Indeed, an

[1]For a general view of the rise in non-regular employment in Japan, see Rebick (2005). Asano et al. (2013) also empirically examine the causes of the increases in the number of non-regular workers, while Hijzen et al. (2015) consider recent changes in employment adjustments in Japanese firms and the influence of the rising number of non-regular workers.

expanding income gap recently observed in Japan is considered as a consequence of this labor market polarization.

Despite this social concern, however, few attempts have thus far been made to empirically examine the differentials between these two employment statuses based on micro data. Among them, Kambayashi and Kato (2012) confirm the general perception that non-regular jobs can be characterized by factors, such as low wages, low job security, and low opportunities for training and development, relative to regular jobs. The coexistence of both types of jobs is a typical property of dual labor markets.[2]

Before the 1990s, the dualism in the Japanese labor market was mainly attributed to differences in firm size. That is, the large-firm sector formed the primary market and the small-firm sector formed the secondary market. Thus, the increase in the share of non-regular employees in recent years suggests the beginning of a new era of labor market polarization in Japan.[3] An essential property of dual labor markets is the rationing of primary jobs, that is, regular jobs. This property implies that labor mobility between the primary (regular job) and secondary (non-regular job) sectors is sluggish. In contrast to the scarcity of research on the different work conditions in these two sectors, a considerable number of studies have examined the transition between these sectors and suggested that mobility is restricted. If this is true, one question arises: when are workers divided into the segmented sectors?

We investigate this question empirically by using micro survey data on employment in Tokyo metropolitan area.[4] Two main explanation arise when considering the timing of the selection of workers. The first is that selection depends on an individual's recent work experience in that holding a non-regular position currently substantially reduces the possibility of finding a regular position in the next job. This would reduce labor mobility between sectors. In this case, selection occurs at each job turnover.

The second explanation is that selection occurs at the point of entry into the labor force. Under this hypothesis, a worker is assigned a different career path according to the type of job he or she secured at the time of entry into the labor market (i.e., just after graduation). If a worker starts working in a non-regular job, it becomes difficult to switch to a regular job even if he or she could obtain one. The permanent differentiation caused by the initial states in the labor market is called "first job effects." Under first job effects, the temporary business-cycle conditions at a worker's time of entry have a permanent influence on his or her lifetime working conditions, such as earnings and employment stability. These phenomena are called "cohort effects." The hypothesis of selection at the point of entry is a convincing argument in Japan, as recruitment is highly concentrated on new school graduates. If such effects exist, the polarization of the labor market leads to more serious disparities in working conditions among workers.

In this study, we aim to distinguish these two mechanisms empirically. One difficulty

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[2]For recent developments in dual labor market theory, see Saint-Paul (1996) and Ishikawa (2002). In particular, the latter concerns the dualism of the Japanese labor market.

[3]Ariga and Okazawa (2011), Kalantzis et al. (2012), and Kitagawa (2014) discuss the possibility that recent changes in the Japanese economy have induced polarization and segmentation.

[4]This area consists of the prefectures of Tokyo, Kanagawa, Chiba, and Saitama.

in investigating these mechanisms is that spurious dependence among one's employment statuses can be caused by his or her unobserved individual attributes. If those time-invariant attributes affect the job decisions throughout one's career, the types of his or her jobs correlate intertemporally. We construct an econometric model that can distinguish genuine state dependence from such spurious dependence.

The remainder of this paper proceeds as follows. Section 2 briefly reviews several aspects of non-regular employment and discusses its recent trends in Japan. We survey the literature on the persistence in the labor market in Section 3 before formulating issues on the intertemporal dependence of states in Section 4. Section 5 presents our empirical strategy to distinguish the sources of persistence. In Section 6, we explain our dataset and examine the property of these data. Then, we specify the equations for the estimation. Section 7 provides the main results, and Section 8 concludes.

2   Non-regular Employment in Japan

Despite the social importance of non-regular employment, a definition of this notion lacks consensus. Kambayashi (2013) summarizes different definitions of non-regular employees based on the statistics published by the Japanese government.[5] He argues that definitions can be divided into three types. The first type classifies employees based on contract length. A typical criterion is whether the contract length (including an indefinite duration[6]) exceeds a certain period (typically, 12 months). Another criterion is whether the contract has a fixed term. Non-regular employment by the latter definition is broader since it includes workers on long fixed-term contracts.

The second type of definition is based on working hours and is close to the general notion of part-time employees. Typically, workers whose weekly working hours are below 35 are distinguished as part-time or short-time employees. However, some surveys do not adopt an absolute standard of working hours and define part-time employees as those whose scheduled working hours are fewer than the working hours prescribed in the formal work regulations of the establishment.

The third type is distinguished based on the title or description used by the workplace. Non-regular employees might be called part-time, temporary, contract workers, and so on. Kambayashi and Kato (2012) find that the distinction based on job title is more representative of working conditions, such as wages, hours of work, probability of quitting, and opportunities for training than contract length. It suggests that classifying workers based on a few dimensions of employment properties, such as working hours or contract length, is somewhat misleading.

Figure 1 shows the trends of the proportion of non-regular workers according to these three definitions. This figure indicates that the proportions and trends differ by definition. The share of workers on short fixed-term contracts, called temporary

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[5]See also Kambayashi (2010).

[6]We use the phrase "indefinite duration" to mean a contract that guarantees employment until the mandatory retirement age.

workers in the survey, increased from 10% in the mid-1980s to 15% in the early 2000s before stabilizing. On the other hand, the shares of both description-defined non-regular workers and persons working shorter hours, called part-time workers in the surveys, have been increasing at a similar rate, even after the 2000s. The share of description-defined non-regular workers reached 35% recently, which was 20% more than the share in the 1980s. The part-time worker ratio is roughly 5% less than the non-regular worker ratio.[7] This means that some non-regular workers work the same number of hours as full-time workers. Further, more than half of non-regular workers now have longer (i.e., spanning more than a year) contracts, and the increased share discussed above is driven by this type of non-regular worker.

Non-regular employment in Japan can be said to be close to the atypical or non-standard employment seen in European countries and the United States. However, the notion of atypical workers is broad even across those countries, and Ogura (2002) compares and summarizes the notion for Japan, European countries, and the United States.[8] According to Ogura (2002), there exists a unique status of Japanese workers that can be categorized as atypical employees. So-called "quasi-part-time" workers tend to work full-time hours; however, they can also include part-time employees whose working hours are shorter than but close to those of full-time employees. A large proportion of these quasi-part-time employees are also thought to work under indefinite-duration or long fixed-term employment contracts. Kambayashi and Kato (2012) state that the proportion of indefinite-duration contract workers (or those that have a minimum one-year contract) is increasing in Japan. Nevertheless, they are not termed regular employees in the workplace because they lack the equivalent opportunities for training or promotion. These workers roughly correspond to the quasi-part-time workers discussed herein. Throughout this paper, we use the term "non-regular" to refer to the Japanese type of atypical employment that is close to the description-defined non-regular employment described above. We adopt this phrasing in order to emphasize the existence of employees with permanent contracts and without the "regular" title/description, which is unique to Japan. Moreover, the wording "non-regular employment" is also widely used in Japan.[9]

3   Literature on the Persistent Initial Conditions in the Labor Market

An essential property of dual labor markets is the rationing of primary jobs. This property implies that labor mobility between sectors is inactive. Indeed, studies of the transition between sectors have suggested that such mobility is actually restricted.

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[7]Note that these ratios are not directly comparable in a strict sense. See the note under Figure 1.

[8]According to Ogura (2002), atypical workers sometimes include the self-employed. As the survey targets employed persons, we use the word "employee" and "worker" interchangeably.

[9]We also use "employment status" to indicate the type of contract, which should be partially implicit (i.e., regular or non-regular employment).

For example, Hirata and Yugami (2011) point out that the transition from non-regular to regular jobs is more sluggish in Japan compared with Germany and the United Kingdom.[10]

The majority of recent research on the transition between employment statuses in Japan has focused on the role of one's early career, especially the first job just after graduating school. Many researchers find that employment status in the first job is responsible for an employee's subsequent employment status for the long-term, based on the positive correlation between employment status in the first job and that in the current job. A representative study in this field is Kondo (2007), who estimates a probit model where the probability of regular employment at present depends on employment status in the first job with other control variables. Kondo's research is notable since it is the first attempt to consider the effects of the initial employment status on the current status by paying attention to the problem of endogeneity, which is typically observed in such a situation. Unobservable individual heterogeneity regarding employment status determination brings about a correlation between the dummy of the first employment status and disturbances, as discussed in detail in Section 4. Following Neumark's (2002) argument of the need for valid instruments to estimate the effects of early job stability on current wages, Kondo (2007) estimates a bivariate probit model on employment status determination by using a local labor market condition index in the year of finishing one's education as an "instrument" for the first employment status.[11] Her results show the strong persistence of employment status. Based on the results of the basic estimation, she concludes that an individual who obtained a regular job upon entering the labor market has about a 50% greater opportunity of working in the regular sector at present and, moreover, that the effects are permanent.

Hamaaki et al. (2013) examine the degree to which the probability of regular employment is affected by employment status several years after graduation in addition to the status of the first job for female workers. They estimate the influences of the initial employment status and/or the employment status k years after graduation on the probability of current regular employment. A multivariate probit estimation is used in the spirit of Kondo (2007). They find that the effects of the employment status just after graduation on the current status decrease gradually and cease about 10 years later. Furthermore, the impact of the employment status in the first job is dominated by that in the next job if workers change jobs within a few years of graduation. That is, the essential factor is the employment status experienced during the early stage of one's career.

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[10]Their notion of non-regular employment corresponds to temporary employment; however, the definitions of temporary employment they use differ across countries. Interestingly, the transition rates they calculate indicate that the transition from regular to non-regular jobs is smaller than the reverse transition in each country. See also Shikata (2011) for the international comparison of the transition from non-regular to regular jobs.

[11]More specifically, Kondo (2007) uses the job opening ratio, namely the ratio of job vacancies to job seekers, of the local prefecture. In the context of bivariate probit modeling, her "instrument" can be interpreted as a variable that satisfies the "exclusion restriction" described in Section 5.

Similarly, Esteban-Pretel et al. (2011a) conduct a structural estimation on a job search model for young male workers in Japan. Their model consists of three states: regular employment, non-regular employment ("contingent employment" in their words), and unemployment. The transition probabilities to regular employment from each of these three initial states are then simulated based on the estimated parameters. They show that the probability of regular employment is higher if one's initial state is unemployment than if it is non-regular employment. However, the effect of the initial state is temporary and the transition probabilities to regular employment converge to the same level within 15 to 20 years.

In sum, although judgments on the permanency of the effects of the initial employment status differ by study, there is no disagreement on their persistence in Japan.

The notion of persistence, not limited to the effect of initial employment status, has also been demonstrated in various aspects of the labor markets outside Japan. It is usually formulated as a model where the current state depends on past states, which is called "state dependence." Heckman (1981a) defines state dependence as the conditional probability that an individual's experience of an event in the future is a function of past experiences. An individual's labor market outcome such as labor force participation, turnover, and unemployment generally shows strong state dependence.[12]

Many researchers examine the state dependence of low-paid employment. Those studies are close to our topic of interest since secondary employment can be characterized by low-paid and unstable jobs.[13] According to Arulampalam et al. (2000), the possible sources of state dependence of unemployment include one's unemployment history as a screening device by employers and the depreciation of human capital during unemployment. The sources of state dependence of low paid employment can be similarly considered. [14]

Although the entire history of states may affect the current state, it is usual to restrict the lag structure to the past few periods, because the effects of previous experience are thought to depreciate over time in most cases. From this perspective, many studies of labor market transition assume a small-order Markov process to describe state dependence. For example, for the UK labor market, Arulampalam et al. (2000) consider state dependence in the unemployment probability by including the one-year lagged unemployment status in the explanatory variables. Similarly, to estimate female labor force participation in the United States, Hyslop (1999) derives a first-order Markov model by using a stochastic dynamic programming model of search behavior. Prowse (2012) also considers the dynamics of female labor force participation in the United Kingdom for full-time and part-time workers. She assumes that states in the past two years affect the

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[12]Arulampalam and Stewart (2009) survey various empirical studies of economic behavior under state dependence. Heckman (1981a,b) deal with the "initial condition problem" in the estimation of dynamic non-linear panel data. This problem arises when unobserved individual heterogeneity exists and the initial observation coincides with the starting value of the examined stochastic process.

[13]See Cai (2014) for the effects in the Australian labor market.

[14]For example, Stewart (2007) examines the state dependence of unemployment and low-paid employment by using British household survey data.

current state. These models reflects the ideas that state dependency operates strongly between time points proximate to each other and its influence diminishes with the distance between the time points. In this paper, we refer to this type of state dependence as "serial state dependence."

A first-order Markov process plays a central role in the analysis of labor market dynamics. The research field on gross labor flows has been devoted to the estimation of a transition matrix in order to describe workers' mobilities among employment states (e.g., employment, unemployment, and not in the labor force).[15][16] This method reflects the view that aggregate flows among states can be characterized sufficiently by using first-order Markov chains. It is natural to think that flows, namely the number of people who move between pairs of states, are determined mostly by stocks, that is, the number of people in each state.[17] If we consider the individual behavior behind the aggregate phenomenon, we see that the incidence of a person being in a certain state is affected by one's previous state. A first-order Markov model also has affinities with stochastic dynamic programming, which is used to analyze labor search models. The solutions usually have the forms of first-order serial state dependence, and they are manipulated for numerical simulations to mimic workers' actual transitions.[18] For example, one empirical research stream investigates how to extend a labor search model based on Mortensen and Pissarides (1994) in order to explain actual unemployment dynamics numerically. Although the evaluation of the explanatory power of the labor search model varies across studies, the idea behind the research is that incorporating realistic factors into a basic labor search model is promising for exploring labor market fluctuations.[19]

The above argument suggests that it is plausible to expect that transitions between employment statuses can be captured as a first-order Markov process. From this viewpoint, the persistence of the first employment status observed in the Japanese labor market can be attributed to strong serial state dependence. However, we must be aware that the persistence can also arise through the above-mentioned "cohort effects"

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[15]Representative early contributions include Abowd and Zellner (1985), Poterba and Summers (1986), and Blanchard and Diamond (1990) for the United States' labor market. Esteban-Pretel et al. (2011b) analyze labor flow dynamics in Japan as well as review the literature on labor flow analysis in the Japanese labor market.

[16]The application of the first-order Markov model is not restricted to labor flow analysis, and it is widely used to analyze social processes in many fields of social sciences. See Bartholomew (1982).

[17]Actually, first-order Markov chains are often used to describe labor market flows. For example, Choi et al. (2014) report that estimated age-specific Markov transition matrices can replicate the actual lifetime profiles of labor force participation and unemployment in the United States quite well.

[18]Esteban-Pretel et al. (2011a) mentioned above, are included in this line of research.

[19]See, for example, Shimer (2005), Mortensen and Nagypál (2007), Hagedorn and Manovskii (2008), and Pissarides (2009) for the United States' labor market. Miyamoto (2011) extends Mortensen–Pissarides' model by introducing the training costs of firm-specific skills to explain the Japanese data. The development of the labor search model also influences studies of labor flows where implications of these models on labor flows are examined empirically by using a continuous-time first-order Markov model. See, for example, Fujita and Ramey (2009) and Shimer (2012). For the Japanese labor market, Lin and Miyamoto (2012) present a recent contribution in this line.

or "first job effects." Although such terms are often used interchangeably, they should be differentiated in the strict sense. We start by focusing on first job effects. Under their definition, the property and quality of the first job upon entering the labor market have long-term effects on the property and quality of future jobs. Since data containing information on the first job are scarce, only a few studies inspect first job effects directly. In this field, Oyer (2006) considers the careers of doctoral-level economists who graduated from leading economics departments in the United States. He examines the long-run effects of the quality of the first job on job quality in the future and finds strong persistence. As possible sources of the persistence, he mentions firm-specific human capital investment, evolving tastes based on experience and the environment, influence from co-workers, signaling effects of past states, and costly search. As mentioned above, Kondo (2007) and Hamaaki et al. (2013) exploit survey data on the employment status in the first job or on the entire job history of individuals to analyze the first job effects of employment status.

Cohort effects attract more attention than first job effects. Indeed, the latter is a prerequisite of the former. In the context of labor mobility, cohort effects refer to the fact that each group of workers who entered the labor market at the same time experiences a distinct transitional process afterward depending on the labor market conditions at the time of entry.[20] The period just after finishing school has a special meaning for one's career. If the labor market conditions affect the employment status or job quality of new entrants and if first job effects exist, then cohort effects arise.

Since cohort effects can be tested by using the year of graduation and labor market conditions (e.g., the unemployment rate) in that year, they are less restrictive regarding the data to be used.[21] Thus, a multitude of studies of cohort effects exist. von Wachter and Bender (2008) report that a part of wage differentials can be attributed to differences in firm-entry cohorts and that cohort effects are persistent in Germany. Kahn (2010) examines the effects of labor market conditions, proxied by the national or local unemployment rate, in the year of entry on the wages, tenure length, and prestige of occupations regarding young male college graduates in the United States. The result shows a long-run negative impact on wages from adverse labor market conditions upon entry. Raaum and Røed (2006) consider the effects of labor market conditions on the probability of being non-employed in Norway. A notable feature of their study is that educational choices and the non-employment probability are estimated simultaneously. They find that the local unemployment rates at the time of entry exhibit a persistent effect on employment prospects, although they find no evidence that such labor market

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[20]The term "cohort effects" can also be used in the broader sense. Ohtake and Inoki (1997) summarize three routes by which a difference in generation can affect an individual's lifetime outcome, namely improvement in the labor productivity of the younger generations by technological progress, the number of workers in a generation, and employment conditions upon entering the labor market. Indeed, Genda (1997), Ohtake and Inoki (1997), and von Wachter and Bender (2008) all consider how the number of workers in a generation affect job properties such as wages. In this paper, we concentrate on cohort effects based on the year of labor market entry unless otherwise noted.

[21]Even if a dataset has no information on graduate years, the graduate year of an individual can be estimated by his or her age and educational background.

conditions affect an individual's educational attainment.[22] Oreopoulos et al. (2012) also discover the persistent effects of the initial local unemployment rates on present wages for Canadian university graduates. They stress that a significant part of wage losses due to adverse entry timing recovers through the process of mobility to higher paying employers; however, this recovery period proceeds gradually. Consistent results are also found by von Wachter and Bender (2008). For male workers in Austria, Brunner and Kuhn (2014) also detect the long-run impact of the initial local unemployment rates on current wages. In addition, they find that the explanatory power of the unemployment rate upon entry reduces when they include variables for the quality of a worker's first employment such as mean compensation, age, or firm size in the explanatory variables. This result suggests the importance of the quality of one's first employment as a source of cohort effects.

Cohort effects have been examined in the Japanese labor market. Early contributions in this field were Genda (1997) and Ohtake and Inoki (1997). For male regular workers (defined by contract length), Ohtake and Inoki (1997) extract a part due to cohort effects from individual wages, years of tenure, and firm size. Good economic conditions at the time of entry are shown to have permanent positive effects on wages and tenure length. Similarly, Genda (1997) finds that long-term wage increases are higher among workers who entered in strong market conditions. The Japanese employment practice known as "lifetime employment" focuses on hiring new graduates and, thus, the job market for displaced workers is underdeveloped. Under such a labor market institution, finding good employment opportunities at the beginning of one's career may display persistent positive effects on a worker's outcome. Genda (1997) and Ohtake and Inoki (1997) both consider the long-term employment practice to be the main source of cohort effects in Japan as the period of search is limited to the time of entry.[23]

Genda et al. (2010) compare the effects of the local unemployment rate in the entry year on current wages, employment probability, and full-time employment probability for Japanese and American male workers. Their conclusion is that adverse labor market conditions at the time of entry induce a persistent reduction in wages and employment probability in Japan, while the effects are less persistent in the United States. In addition, for the Japanese labor market, they show that a recession at time of entry reduces the probability of having a full-time job in the long run, which negatively affects wages. The fact is consistent with the evidence of first job effects found by Kondo (2007) and Hamaaki et al. (2013).

As shown above, various studies in many developed countries present evidence of persistent or even permanent entry-time cohort effects on an individual's labor market outcomes. The sources of cohort effects include job search, human capital accumulation

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[22]Raaum and Røed (2006) estimate the probability of non-employment conditional on the one-year lagged state of non-employment in order to consider state dependence. Their concern on the point is close to ours, as we explain in Section 4.

[23]Genda (1997) and Ohtake and Inoki (1997) show that the long-term employment system also creates significant cohort effects owing to the generational size in Japan.

(e.g., Kahn, 2010; Oreopoulos et al., 2012), and statistical screening (e.g., Genda et al., 2010). Note that these explanations can also be applied to explain the sources of serial state dependence. A critical difference is that the early period in one's career plays a special role in cohort effects. Oreopoulos et al. (2012), for example, explain that the job search cost increases with age and that prolonged search periods in a recession cause a persistent loss in firm- and industry-specific human capital accumulation by new entrants. Genda et al. (2010) also state that starting one's career in a non-regular job signals low productivity, especially for high school graduates in the prevalent school-based hiring system in Japan. This non-regular status makes it difficult for non-regular workers to switch to regular jobs in the future. The employment status in one's youth can also play a special role under the information cascade, which refers to a situation in which an employer follows the preceding employer's decision independent of his or her private signal. Thus, if workers were hired in non-regular jobs at the beginning because of adverse economic conditions, employers might only offer them opportunities of non-regular employment afterward.[24]

Recall that the argument on cohort effects premises the existence of first job effects. If first job effects exist, the initial state directly influences the current state in a way different from any other past states. Cohort effects are generally identified by the observed positive correlation between the first and current states or the entry-year economic conditions and current outcome. However, the correlation can evolve because of either serial state dependence or cohort effects. Although these two phenomena are quite different, previous studies have paid insufficient attention to distinguishing them and have scarcely considered them simultaneously. We deal with this problem in the next section.

4   Long-term Consequences of Employment Status upon Entry

As discussed in the previous section, the correlation between the first and the current employment status can evolve because of either serial state dependence or first job effects. However, the two phenomena are quite different. Suppose that current employment status depends on recent preceding statuses (i.e., serial state dependence). In addition, suppose that there is no direct effect from the initial to the current status. If serial state dependency is strong, the initial status can affect the current status in the long run by repeating the serial-state-dependence sequence. The first job does not play a special role. Even if every worker follows the same transition process irrespective of the employment status of the first job, the initial and the current employment statuses will be correlated for a considerable period. On the other hand, in the case of first job effects, the initial state directly influences the current state in a way different from any other past states.

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[24]See Kübler and Weizsäcker (2003) for information cascades in the case of the employment decision.

To clarify this argument, let us consider a two-state Markov transition model of job turnover. Our empirical analysis concentrates on the transition between employment statuses accompanied by a job change. In addition, it excludes the transition into and out of the labor force.[25]

Thus, each worker belongs to one of the employment statuses represented by

$$\begin{cases} 1 = \text{regular employee} \\ 0 = \text{non-regular employee.} \end{cases}$$

Let us assume that a worker's transition between these employment statuses follows the transition matrix:

$$P = \begin{pmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{pmatrix},$$

where p_{ij} represents the probability of moving status i to status j, that is, a conditional probability $p_{ij} = \Pr\{J_m = j | J_{m-1} = i\}$ $(i,j = 0,1, m = 1,2,\cdots)$. Here, J_m denotes the employment status just after m-th job change, and J_0 denotes the initial employment status. We assume that the transition follows a first-order Markov process, except the possible effects of first job. As discussed in Section 3, a first-order Markov process can be justified empirically and theoretically to describe a variety of dynamic activities in the labor market.

Suppose that each worker moves following the common P. Then, the conditional probabilities p_{ij} among workers are the same irrespective of their values of J_0. That is, the initial employment status does not affect the current transition probability. Let us write this situation as $p_{ij}|_{J^0=0} = p_{ij}|_{J^0=1}$ $(i,j=0,1)$.[26] In this case, the probability of regular employment at a certain time depends on the initial employment status only indirectly through the dependence on its previous state in each period: the initial employment status affects the second employment status, which in turn affects the third and so forth. This effect gradually declines over time.

This can be formally stated as follows.[27] Let us denote J_m's distribution as

$$\pi_m = (\Pr\{J_m = 0\}, \Pr\{J_m = 1\}), \quad m = 0,1,2,\ldots.$$

The process that starts from the initial distribution π_0 with the transition matrix P reaches a distribution $\pi_m = \pi_0 P^m$ after m job changes. It is known that if P is irreducible, that is, every state is reachable from the other states, and aperiodic, then

there exists a unique stationary distribution π (a row vector) that satisfies the condition $\pi P = \pi$ and P^m converges to $\iota\pi$ as $m \to \infty$, where ι is a column vector of ones. Therefore, for any initial distribution π_0,

$$\lim_{m\to\infty} \pi_m = \lim_{m\to\infty} \pi_0 P^m = \pi_0 \lim_{m\to\infty} P^m = \pi_0 \iota\pi = \pi,$$

where $\pi_0\iota = 1$ since the sum of probabilities equals one. This implies that

$$\lim_{m\to\infty} \Pr\{J_m = k|J_0 = 0\} = \lim_{m\to\infty} \Pr\{J_m = k|J_0 = 1\}, \quad k = 0, 1.$$

In sum, in the absence of first job effects, we find a significant correlation between the current and the initial employment statuses only if the number of job changes since entry is small and/or the probabilities of staying in a certain state, that is, the diagonal elements of P, are large. The initial employment status does not play any special role here. A process starting from state k at entry has the same transitional characteristics as a process starting from state k in any other period.

This is clearly different from the meaning of first job effects, as we have already examined. In the presence of first job effects, working a non-regular job in one's youth reduces the probability of finding a regular job persistently. In the context of the Markov transition model, this can be interpreted as the situation where workers are confronted with distinct transition matrices P, depending on their initial status J_0. More concretely, the probabilities of moving to regular jobs for workers who started their career with non-regular jobs are lower than the corresponding probabilities for those who started with regular jobs: $p_{01} \mid_{J^0=0} < p_{01} \mid_{J^0=1}$. The former workers also lose regular jobs by turnover more frequently than the latter: $p_{10} \mid_{J_0=0} > p_{10} \mid_{J_0=1}$. Consequently, the probabilities of having regular jobs differ between these two groups even long after job market entry, and this distinction does not disappear over time. That is, since the transition probabilities, and hence the limiting (stationary) distributions,[28] depend on their initial employment statuses, we have

$$\lim_{m\to\infty} \Pr\{J_m = k|J_0 = 0\} \neq \lim_{m\to\infty} \Pr\{J_m = k|J_0 = 1\}, \quad k = 0, 1.$$

The employment status upon entry is in turn exposed to the labor market conditions at that time. Therefore, the common experience among the same generation induces cohort effects.

5   Empirical Strategy

This section describes the multivariate probit model used herein to inspect first job effects. Following the argument in the preceding sections, we adopt a first-order Markov process to describe serial state dependence.

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[28]In the 2 $\times$ 2 transition matrix case here, the stationary distribution is given by $\pi = (p_{10}/(p_{10} + p_{01}),\ p_{01}/(p_{10} + p_{01}))$.

Let J_i, J'_i, and J^0_i denote the current, previous, and initial employment status of worker i ($i = 1, \ldots, N$), respectively. Note that we have changed the notation slightly. Now, suppose that J_i is determined by a binary choice model:

$$J_i = 1\left(\alpha_1 J^0_i + \beta_1 J'_i + \gamma^\top_1 X_i + u_i > 0\right), \tag{1}$$

where $1(\cdot)$ is the indicator function that equals one if the statement in the parenthesis is true and zero otherwise, and X_i is a vector of the exogenous variables affecting the determination of the current status. The disturbance term u_i is assumed to be normally distributed with mean 0, and its variance is normalized to one. Although the normality of the error is not essential for the argument in this section, it is necessary for the maximum likelihood estimation of the model.

For the moment, we assume that the past employment statuses J^0_i and J'_i in addition to X_i are also exogenous. (We relax this assumption later.) Then, under the normality of u_i, (1) is a standard probit model, and we have

$$\begin{aligned}
&\Pr\{J_i = 1 | J'_i = j'_i, J^0_i = j^0_i, X_i = x_i\} \\
&= \Pr\{u_i > -\alpha_1 J^0_i - \beta_1 J'_i - \gamma^\top_1 X_i | J'_i = j'_i, J^0_i = j^0_i, X_i = x_i\} \\
&= \Pr\{u_i > -\alpha_1 j^0_i - \beta_1 j'_i - \gamma^\top_1 x_i\}, \tag{2}
\end{aligned}$$

where $j^0_i, j'_i = 0, 1$ and x_i is a realization of X_i. The last equality follows from the exogeneity of the conditioning variables. Similarly, $\Pr\{J_i = 0 | J'_i = j'_i, J^0_i = j^0_i, X_i = x_i\} = \Pr\{u_i \leq -\alpha_1 j^0_i - \beta_1 j'_i - \gamma^\top_1 x_i\}$. Therefore, if and only if $\alpha_1 = 0$, this conditional probability does not depend on the value of J^0_i, and we have

$$\Pr\{J_i = j_i | J'_i = j'_i, J^0_i = 0, X_i = x_i\} = \Pr\{J_i = j_i | J'_i = j'_i, J^0_i = 1, X_i = x_i\},$$
$$j_i, j'_i = 0, 1, \tag{3}$$

given the realized value of X_i. Note that this corresponds to the case $p_{ij}|_{J_0=0} = p_{ij}|_{J_0=1}$ ($i, j = 0, 1$) in the job transition model discussed in the previous section, and can be interpreted as the serial state dependence case. On the contrary, if and only if $\alpha_1 \neq 0$, then the equality in (3) does not hold and first job effects exist, which corresponds to the case $p_{ij}|_{J_0=0} \neq p_{ij}|_{J_0=1}$ ($i, j = 0, 1$).

Thus, by estimating the probit model in (1) and examining whether $\alpha_1 = 0$, we can find the intrinsic relationship between the initial and the current employment statuses. If the null hypothesis $\alpha_1 = 0$ is rejected, then (3) is denied, and hence, first job effects are detected. Otherwise, (3) is verified and the observed correlation between J^0_i and J_i should be caused by serial state dependence.

The assumption that the past states J^0_i and J'_i are exogenous may be unsuitable in practice. The typical endogeneity problem may exist, since individual preferences and abilities related to the employment status included in the disturbance u_i generally influence the choice of employment status throughout one's life.[29] If that is the case,

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[29]The factor in a disturbance corresponds to the time-invariant individual effect in panel data models.

u_i is correlated with both J_i^0 and J_i' in (1), and therefore, J_i^0 and J_i' are endogenous although they are predetermined. For example, workers with a preference for flexible working or a job without transfer tend to find a non-regular job. Heckman (1981a) calls such factors individual heterogeneity, under which spurious state dependence of the current state on the past state might be observed. He also points out the need to distinguish genuine state dependency, which he calls structural dependency, from spurious dependency.

To deal with the possible endogeneity of the past employment statuses, we must also consider the equations generating J_i^0 and J_i', and estimate the whole system of equations by using the maximum likelihood method. Unfortunately, however, it is difficult to construct a general and still estimable model for this purpose. (The reason is explained in footnote 30.) Hence, we restrict our attention to the case in which individuals change their jobs exactly twice. In this case, we can postulate that J_i^0 and J_i' are generated by

$$J_i' = 1\Big(\alpha_2 J_i^0 + \gamma_2^\top Y_i + v_i > 0\Big) \tag{4}$$

and

$$J_i^0 = 1\Big(\gamma_3^\top Z_i + w_i > 0\Big), \tag{5}$$

where $1(\cdot)$ is the indicator function as before, and Y_i and Z_i are the vectors of the exogenous variables affecting the determination of individual i's previous and first employment statuses, respectively.

Note that since we have assumed that J_i in (1) depends on the previous employment status J_i', J_i' in (4) should depend on the one before the previous employment status, J_i'', say, as well as the first employment status J_i^0 in order for the two equations to be consistent. However, for individuals who changed their jobs precisely twice, J_i'' coincides with J_i^0, and therefore, (4) is the appropriate equation for the previous employment status for such individuals.[30] Equation (5) has only exogenous explanatory variables because when individuals choose their first jobs, they have no past job experiences. Thus, we find it reasonable to assume that for the individuals who changed their jobs exactly

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[30]In general (for individuals whose turnover is higher than two), since we have assumed the possibility that the determination of employment status depends on both the previous and the initial statuses as in (1), the same structure should appear in every determination equation of the employment status except the first and second ones.

To be concrete, consider the status determination equation for the m-th job ($m \geq 3$), on the right-hand side of which the $(m-1)$-th employment status has to appear as an explanatory variable, just like J_i' in (1). We need, in turn, another equation for the determination of the $(m-1)$-th employment status and must have the $(m-2)$-th employment status on the right-hand side. In the same manner, we need to define the status determination equations for the $(m-2)$-th, $(m-3)$-th, ..., 3rd employment statuses. The first and second employment status equations have different structures as discussed in the text.

Consequently, we have to know the entire history of job changes to estimate such a general system. On the other hand, the dataset we use in this study contains information only on the initial, previous, and current employment statuses. Moreover, even if complete information on the history of job changes is available for each worker, we need the system consisting of m equations for the respondents who changed their jobs $m-1$ times. It is practically difficult to estimate such a (potentially) large system.

twice, the employment status determinations are described by the system of equations (1), (4), and (5). Moreover, the dataset we use in this study contains information only up to the second job change, as explained in detail in Section 6. Given the feasibility of estimation and the availability of data, we restrict our analysis to the case where workers changed jobs exactly twice.

The disturbance vector $(u_i, v_i, w_i)^\top$ in (1), (4), and (5) is assumed to have a trivariate normal distribution with mean vector 0 and variance–covariance matrix Σ. The diagonal elements of Σ are normalized to unity to identify the model. Thus, we have a trivariate probit model with endogenous binary explanatory variables. The recursive structure of the model, that is, no endogenous explanatory variable in (5), only one such variable in (4), and two in (1), allows us to compute the likelihood function. The derivation of the likelihood function and its practical implication are given in the Appendix. By applying the maximum likelihood method, we can consistently estimate the parameters of the system.

Now, consider the implication for first job effects in the trivariate model above. Define a random vector $G_i = (X_i^\top, Y_i^\top, Z_i^\top)^\top$ and a real vector $g_i = (x_i^\top, y_i^\top, z_i^\top)^\top$ to simplify the notation. Then, the equality of the conditional probabilities corresponding to (3) is

$$\Pr\{J_i = j_i | J_i' = j_i', J_i^0 = 0, G_i = g_i\} = \Pr\{J_i = j_i | J_i' = j_i', J_i^0 = 1, G_i = g_i\},$$
$$j_i, j_i' = 0, 1. \quad (6)$$

As before, this equality does not hold, that is, first job effects exist, if $\alpha_1 \neq 0$. Hence, it is still essential to examine whether $\alpha_1 = 0$ in the present setup. However, it should be noted that $\alpha_1 = 0$ does not necessarily imply (6) if the variance–covariance matrix Σ is not diagonal.[31] To see this, suppose $\alpha_1 = 0$ and write the first equality in (2) (with $X_i = x_i$ replaced by $G_i = g_i$) separately for $j_i^0 = 0$ and 1:

$$\Pr\{J_i = j_i | J_i' = j_i', J_i^0 = 0, G_i = g_i\} = \Pr\{u_i > -\beta_1 J_i' - \gamma_1^\top X_i | J_i' = j_i', J_i^0 = 0, G_i = g_i\},$$
$$\Pr\{J_i = j_i | J_i' = j_i', J_i^0 = 1, G_i = g_i\} = \Pr\{u_i > -\beta_1 J_i' - \gamma_1^\top X_i | J_i' = j_i', J_i^0 = 1, G_i = g_i\},$$
$$(7)$$

where $j_i, j_i' = 0, 1$. The second equality in (2) (with $X_i = x_i$ replaced by $G_i = g_i$) no longer holds because the conditional distribution of u_i is not the standard normal, the assumed unconditional distribution, if Σ is not diagonal, and hence, J_i' and J_i^0 are endogenous. The two conditional probabilities above generally differ since the conditional distributions of u_i given $J_i^0 = 0$ and that given $J_i^0 = 1$ are different if u_i is correlated with v_i and/or w_i. Suppose, for example, that u_i is positively correlated with w_i. Then, given $J_i' = j_i'$ and $G_i = g_i$, u_i tends to take a higher value when $J_i^0 = 1$, that is, $w_i > -\gamma_3^\top z_i$, than when $J_i^0 = 0$, that is, $w_i \leq -\gamma_3^\top z_i$. Hence, the conditional probability of $J_i = 1$, that is, $u_i > -\beta_1 j_i' - \gamma_1^\top x_i$, is higher when $J_i^0 = 1$.

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[31]If Σ is diagonal, then the disturbances u_i, v_i, and w_i are independent. In this case, the variables J_i' and J_i^0 are exogenous in (1), and the argument in the first half of this section applies.

The case in which (6) fails to hold because of the correlations among the disturbances u_i, v_i, and w_i, although $\alpha_1 = 0$, corresponds to spurious state dependence in the terminology of Heckman (1981a), as discussed above. An individual who preferred to find a non-regular job upon labor market entry, for instance, would prefer to have a non-regular job at present, too. We can differentiate this case from the first job effect case in which (6) does not hold because of $\alpha_1 \neq 0$, since the variance–covariance matrix Σ of the disturbances as well as the coefficient parameters in the trivariate probit model are estimated consistently by using the maximum likelihood method.

In the literature, the following type of bivariate system has often been estimated: the initial status equation (5) and the current status equation

$$J_i = 1\left(\alpha J_i^0 + \gamma^\top X_i + u_i\right), \tag{8}$$

where the initial regular employment opportunity increases the probability of regular employment at present if α is positive. In practice, assuming α to be a fixed coefficient is considered too restrictive since it means that first job effects should be either permanent or non-existent. Therefore, typically, researchers allow α to be a function of τ, namely the time elapsed since the beginning of a worker's first job.[32] Previous studies have often detected α as being a decreasing function of τ; however, the declining speed of the effect of J_i^0 is slow. These results have been interpreted as evidence that the first job exhibits long-lasting effects. As we have already seen, however, a bivariate model, such as (5) and (8) cannot distinguish serial state dependence from first job effects.

6 Data Description and Empirical Specification

6.1 Working Person Survey (WPS)

The data we use are taken from the Working Person Survey (WPS) conducted every two years in September by the Recruit Works Institute. The purpose of the WPS is to reveal the status of working individuals and their attitudes towards employment. To this aim, the survey asks respondents about subjective recognition and objective attributes related to their present and past jobs. The key questions, for example, position, age, and working hours, remain unchanged, but various other questions change across the survey years.

The data are gathered by an online survey via a dedicated website. The sample size is about 10,000, and participants are chosen by random sampling from each population segmented by gender, age, and employment area. Subjects are resampled every survey year. Thus, the WPS does not have a panel structure.

The coverage of the WPS is as follows. First, respondents must be aged between 18 and 69 years, but students are excluded.[33] Second, respondents must have worked at

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[32]See, for example, Genda et al. (2010), Kahn (2010), and Hamaaki et al. (2013) although their model specifications are not the same as (8).

[33]Only the 2014 survey contains individuals aged over 59 years.

least one day during the past week in the month before the survey. Third, respondents must be a regular employee, contract or entrusted employee, temporary worker, part-time worker, dispatched worker, outsourced worker, or freelancer; self-employed workers are excluded. Fourth, respondents must work in the Tokyo metropolitan area.

Although the WPS is not a panel survey, it has many retrospective questions, especially regarding past jobs. In this study, we adopt the survey results from 2012 and 2014 since only these surveys have information on the first and previous jobs necessary for our empirical method. The questionnaire asks about working patterns in the current job as well as in the initial job, that is, the first job after finishing school. In addition, the WPS asks whether respondents have any experience of changing jobs. If they have, it asks about working patterns in the previous job, that is, the job just before the current job. We then define a binary index for each employment status, which equals one if a respondent is a regular employee and zero otherwise.[34] The indices for the current, previous, and initial employment statuses are the explained variables, J_i^0, J_i', and J_i, in the trivariate probit model (1), (4), and (5), respectively.[35]

6.2 Employment Status Transition

In the WPS dataset, respondents' educational backgrounds are classified into seven categories: junior high school, senior high school, vocational school, junior college, technical college, college or university, and graduate school. We refer to individuals who belong to one of the last two categories simply as "university graduates" and the remaining individuals as "high school graduates." Table 1 summarizes the WPS respondents' employment status transitions from the initial or previous job to the current job by gender and by the grouped educational backgrounds stated above. The respondents who have never changed jobs are excluded, and the initial and previous jobs are the same for those who have changed their jobs only once. In the two columns corresponding to each combination of gender and educational background, each row reports the proportions of the individuals who moved to non-regular or regular current jobs among those who were non-regular or regular employees in their initial or previous jobs. The percentages in parentheses indicate employment status transitions for workers who experienced turnover just twice. (The reason we consider this case separately is given below.)

The upper panel of Table 1 shows the results for male workers. Let us first examine the male workers' transitions from the initial job to the current one. Seventy-three percent of the high school graduates and 81% of the university graduates who started

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[34]To be more precise, the 2012 survey asks about the working patterns of the initial job in a way unlike the 2014 survey. The question in the 2012 survey is divided into two parts: working patterns and contract types. For "working patterns," the choices are "full-time (weekly working hours more than or equal to 35)" or "part-time (weekly working hours less than 35)." For "contract types" (actually contract length, in this case), the choices are "indefinite-term" and "fixed-term." These subquestions do not correspond to the question adopted in the 2014 survey (or to the questions on previous and current jobs in the 2012 survey). We use these contract types to construct an index for the initial employment status, which takes one if a respondent has an indefinite-term contract and zero otherwise.

[35]The WPS asks for just one employment status for each job taken.

working in regular jobs hold regular jobs at present, too. On the other hand, both are less likely to have regular current jobs if they engaged in non-regular first jobs. The proportion of non-regular to regular transitions is 49% for high school graduates and 58% for university graduates. In either group, the decrease is more than 20 percentage points compared to the regular to regular transitions. It could suggest that the initial employment status significantly affects the current employment status.

Proceeding to the male workers' transitions from the previous job to the current one, we find rather strong persistency in the regular employment status: the proportions of the regular employees in the current jobs among those who were regular employees in their previous jobs are 82% and 86% for high school and university graduates, respectively. Observe also that the transitions from non-regular previous jobs to regular current jobs are more likely in percentage terms to occur than the other way round. The percentages of the non-regular to regular (regular to non-regular) transitions are 33% (18%) for high school graduates and 42% (14%) for university graduates. As a result, if there are similar numbers of regular and non-regular male workers in the beginning, we will observe a tendency for them, either high school or university graduates, to move into regular employment as the transitions are repeated.

The lower panel of Table 1 shows the results for female workers. Looking at the initial to current transitions for women, the percentages of the non-regular to regular transitions are smaller than those of the regular to regular ones as in the male case. However, we find that the differences are significantly smaller in magnitude than those in the male case, that is, 8 percentage points $(31\% - 23\%)$ for high school graduates and 4 percentage points $(42\% - 38\%)$ or university graduates. Hence, the initial employment status might not affect the current one for women as much as for men.

We also find a distinction between genders in the previous to current transitions, that is, strong persistency of non-regular, rather than regular, employment status is observed for women. The proportions of female workers who have non-regular current jobs among those who previously had non-regular jobs are 85% for high school graduates and 79% for university graduates. Furthermore, the regular to non-regular transitions occur much more often for women than for men. The percentages of the regular to non-regular transitions are 51% and 40% for female high school and university graduates, respectively. Thus, if there are similar numbers of regular and non-regular female workers in the beginning, we will observe a tendency for them to change to non-regular jobs in contrast to the case of male workers.

Note that in the preceding arguments we did not consider the individual heterogeneities of workers, for example, their attributes, or the economic conditions affecting workers' and employers' decisions, such as the unemployment rate in the relevant year. The employment status determination is naturally considered to depend on such factors, and hence, the casual observations we made above may be misleading. In the following, we investigate the mechanisms behind the facts shown in Table 1 more closely, by making use of the statistical model introduced in the previous section.

We mention some caveats before proceeding. In order to make our statistical analysis

possible, we restrict our attention to the subsample in which individuals change their jobs exactly twice, as mentioned in Section 5. The figures in parentheses in Table 1 indicate the percentages of the transitions for such workers, which are close enough to the counterparts for the larger sample consisting of workers who experienced turnover at least once. This could be interpreted as supporting our expectation that restricting the sample would not introduce too a harmful bias. On the contrary, the loss of efficiency in the estimation caused by dropping many respondents from the sample might be rather serious. Table 2 shows the distribution of the amount of turnover by gender and status of initial employment. We find that the size of the subsample used for our estimation is only less than 15% of the whole sample either for male or female workers. It is, however, difficult to construct and estimate a more general model that can allow for any number of job changes as detailed in footnote 30.[36]

6.3   Specification of the Estimated Equation

This subsection explains the specification of each equation in the system, namely (1), (4), and (5). Let us start with the initial state equation, (5). Since it is the first choice of employment status, the equation does not contain past employment status on the right-hand side. Therefore, the explanatory variables are all exogenous.

Our choice of exogenous variables Z_i is divided into two groups. The first group represents workers' abilities or possible signals for them. We include educational background as such a variable. We take junior high school graduates as the base category.[37] Another proxy for ability is respondents' self-assessment of their record in the final grade of junior high school. They choose an answer from five ranked alternatives: upper, upper-middle, middle, lower-middle, and lower. We then construct four dummy variables for which the lower rank is the base.

The second group of variables concerns situations or circumstances that are thought to be exogenous to workers. Age and marital status when a respondent found his or her first job are included. Marital status is a dummy variable that takes one if respondents were married at the time of finding their first job and zero otherwise. It is hardly conceivable that workers adjust these factors in response to the statuses of employment

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[36]Table 2 shows that individuals whose number of job changes equals zero or one account for the most of those excluded from the sample used for our estimation. To see how these proportions of individuals may affect the results, we estimate the first state equation (5) for a sample including workers who changed their jobs once or less in addition to those who changed their jobs twice. Furthermore, we estimate the bivariate system of equations (4) and (5) for a sample including individuals who changed their jobs once or twice. The estimated coefficients in either case are generally close to those in the corresponding equations of the trivariate system presented in Section 7. In particular, all the signs of the significantly estimated coefficients in both cases are the same as the corresponding ones in the trivariate system. Thus, excluding the individuals who experienced turnover once at most does not seem to cause a serious problem.

[37]The 2014 survey asks about education levels in two ways. One is the school from which a respondent graduated before starting his or her first job. The other is the final academic background (at the time of the survey). These questions consider the possibility of recurrent education. We use the former for the initial state equation and the latter for others.

they can engage in. In addition, the unemployment rate at the time of entry is included. This represents the business-cycle conditions reflected in the labor market.[38] Workers of the same generation are affected by the same business-cycle conditions when they search for their first jobs. Thus, the unemployment rate in the initial state equation is a key variable to detect cohort effects.

Next, let us examine the explanatory variables in the previous state equation (4). These contain the initial state J_i^0, which is thought to be endogenous. The other explanatory variables Y_i are exogenous and include educational background and self-assessment of junior high school record as proxies for ability. Age, marital status, and unemployment rate at the time of finding the previous job represent uncontrollable events for respondents. Hence, these variables have the same meaning as Z_i in the initial state equation. In addition, the number of months from the end of the initial job to the beginning of the previous job is considered as an explanatory variable.[39] This variable measures the effect of the duration unemployed or out of the labor force.

Finally, let us turn to the current state equation (1). Both the previous J_i' and the initial J_i^0 appear on the right-hand side. As explained in Section 5, if the initial state influences the current state only because it depends on the previous state, the initial status J_i^0 should lose its explanatory power when the previous status J_i' is included. If J_i^0 still shows a significant effect, it means that the early sate of one's career affects the future transition directly. The other variables correspond to those in the previous state equation.

To sum up, for the exogenous explanatory variables X_i, Y_i, and Z_i, we include a worker's attributes and characteristics that may influence the determination of employment status as well as a variable to represent labor market conditions, that is, the annual unemployment rate. Some of the exogenous variables such as self-assessment of of junior high school record are common in all equations, while the other exogenous variables appear only in one. For instance, the unemployment rate in the year of transition to the current job appears as an explanatory variable only in the current state equation. Thus, it may be regarded that some exclusion restrictions are imposed on each equation in the system. Unlike linear simultaneous equation models, these exclusion restrictions are not needed to identify the multivariate probit model. Nevertheless, the existence of these restrictions might help obtain good estimates in our non-linear model.

The initial state J_i^0 has both direct and indirect effects. In the context of the job-change model presented in Section 4, the indirect effect arises through J_i' and decreases at a rate of convergence of P^t. On the contrary, the direct effect alters the transition matrix P. If the initial condition differentiates the transition matrix P permanently, the direct effect does not diminish. More realistically, the direct effect itself may also

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[38]We use the annual nationwide unemployment rate taken from the Labour Force Survey issued by the Ministry of Internal Affairs and Communications. We do not use the local unemployment rate since it is available only from the 1980s. Our sample contains those who finished their academic careers before the 1980s. Indeed, the oldest graduated in the 1950s.

[39]This represents the period between the first and second jobs, since we restrict subjects to workers who experienced just three jobs.

reduce its influences on the current state. To take this possibility into account, we estimate the current and previous state equations including the cross terms between the initial employment status dummy J_i^0 and external labor market experience. Here, external labor market experience is defined as the number of years from the starting year of the first job to that of the current or previous job. A negative coefficient of this cross term means that the initial job becomes less influential in the job determination at a later period since entry. Such a decline in first job effects may occur because employers attach less importance to one's early career as information of ability when recruiting regular employees or because human capital accumulated within the initial regular job depreciates over time. In addition, we allow for different responses to the initial employment status according to educational background. Several previous studies suggest that the size and persistence of cohort effects, or first job effects, differ according to workers' educational backgrounds.[40] Finally, we should consider the differences in the determination of employment status between genders. Female workers are thought to select non-regular jobs more voluntarily than male workers since female workers often participate in the labor market secondarily in Japan. Therefore, we estimate the equations separately by genders.

The above consideration leads to the following modifications to (1) and (4), respectively:

$$J_i = 1\left[\left\{(\alpha_{11} + \alpha_{12}D_i) + (\delta_{11} + \delta_{12}D_i)\tau_i\right\}J_i^0 + (\beta_{11} + \beta_{12}D_i)J_i' + \gamma_1^\top X_i + u_i > 0\right] \quad (9)$$

and

$$J_i' = 1\left[\left\{(\alpha_{21} + \alpha_{22}D_i) + (\delta_{21} + \delta_{22}D_i)\tau_i'\right\}J_i^0 + \gamma_2^\top Y_i + v_i > 0\right], \quad (10)$$

where τ_i is defined as years from the beginning of the first job to that of the current job, τ_i' as years from the beginning of the first job to that of the previous job, and D_i as an education dummy that takes one if a respondent is a "university graduate" defined in the previous subsection and zero otherwise. As a result, our estimated system of equations consists of (9), (10), and (5).

Our main concern is equation (9). (We cannot extract first job effects by examining the coefficients of J^0 in (10), as discussed in Section 5.) If the coefficient of J_i^0, that is, $\alpha_{11} + \alpha_{12}D_i$, is positive in (9), first job effects exist as explained in Section 5. The probability of regular employment is higher if one's initial employment status is regular. On the contrary, if the coefficient of the cross term $\tau_i \cdot J_i^0$, that is, $\delta_{11} + \delta_{12}D_i$, is negative, this indicates a decreasing influence of first job effects. The effect of the first employment status on the current employment status declines as one's years of experience increase. The total amount of survived first job effects for a worker with external experience τ_i is given by $(\alpha_{11} + \alpha_{12}D_i) + (\delta_{11} + \delta_{12}D_i)\tau_i$.

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[40]See, for example, Genda et al. (2010).

7 Empirical Results

7.1 Probit Estimation

Table 3 shows the results of the estimation described in Section 6. The results for the male and female respondents are reported in Columns 1–3 and Columns 4–6, respectively. Note that the current job corresponds to one's third job since we restrict subjects to workers who changed jobs exactly twice.

Columns 1 and 4 show the coefficient estimates of the current state equation (9). We describe only the results for high school graduates, that is, $D_i = 0$. As we see shortly, however, all the coefficients of the interactions with D_i are statistically insignificant for both men and women.[41] Hence, the following statements apply, regardless of workers' educational background.

The coefficient β_{11} of J_i', a dummy for the previous employment status, is significantly estimated and positive for both genders, suggesting that the current employment status depends on the previous status. That is, serial state dependence is observed. The most notable finding here is that the coefficient α_{11} of J_i^0, a dummy for the initial employment status in (9), is also significantly estimated and positive for both male and female respondents despite introducing the previous status J_i' as an explanatory variable. As explained in Section 5, this fact means that the initial employment status directly affects the current employment status, not merely through a succession of turnovers. This finding implies that the initial status alters the subsequent transition process. The estimated coefficient δ_{11} of the cross term between J_i^0 and external experience τ_i is significantly negative for men. That is, first job effects decrease over time. However, the estimated coefficient is relatively small in absolute value compared with that of J_i^0. This finding suggests that first job effects may be long lasting. For women, the estimated coefficient is not significantly different from zero, and thus, first job effects do not attenuate.

As mentioned above, none of the coefficients of the cross terms with the dummy for university graduates, that is, $D_i \cdot J_i^0$, $D_i \cdot \tau_i \cdot J_i^0$, or $D_i \cdot J_i'$ in (9), is significantly estimated, irrespective of gender. Genda et al. (2010) find a large difference in the effects of entry conditions according to workers' educational backgrounds. Our results thus contrast with their findings, perhaps because the subjects in our dataset are restricted to residents in the metropolitan area, in which the population of university graduates is larger than that in other areas. Thus, the market for workers with a university degree is more competitive in the metropolitan area, suggesting that this group may not enjoy an educational advantage. In terms of the coefficients of the variables reflecting personal conditions at the time of taking the current job, we find that the estimated coefficient of age has a negative sign but is insignificant. Further, the coefficient of the interval between the two jobs is significantly estimated with a negative sign and suggests that the probability of being a regular worker declines as the period of non-

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[41] In this study, we judge the significance of estimated parameters based on the 5% level unless otherwise noted.

employment lengthens. The estimated coefficients of the educational dummies display no significant relation to the current employment status. Educational level is thought to represent a worker's ability, or may work as a signal of ability, and thus affect the determination of employment status. However, the results show no evidence of such a hypothesis. A junior high school record generally does not seem to signal a worker's ability since employers cannot observe it. Therefore, if the variable is effective, it reflects a worker's innate or acquired general ability. However, we cannot find such evidence. These findings are common for both genders. The estimated coefficient of marital status displays a significant positive sign for men and a negative sign for women. This finding suggests that a male (female) worker seeks a regular job more (less) often if he (she) is married. The reverse signs of marital status seem natural in Japan since a sizable proportion of married women are homemakers and thus when they enter the labor force, they do so only in a secondary capacity. The unemployment rate at the time of finding the current job does not influence the determination of employment status for either gender. Overall, the estimation results in Columns 1 and 4 suggest that the initial and previous employment statuses are more influential than the labor market conditions on the probability of finding a regular job.

Next, we present the results of the other two equations. Although they are estimated simultaneously to deal with the endogeneity problem in the current state equation, it is useful to examine the appropriateness of the system by checking the estimated coefficients in these two equations. More importantly, cohort effects can be confirmed by examining the initial state equation as described in Section 6.

The results regarding the previous state equation (10) for men and women are shown in Columns 2 and 5, respectively. The previous job is the second job for the subjects in our sample. The estimated coefficient of the initial employment status, J_i^0, is positive and that of the cross term with the external experience, $J_i^0 \cdot \tau_i'$, is negative. The estimated coefficient of J_i^0 is significant for each gender. That of $J_i^0 \cdot \tau_i'$ is significant only for men. The estimated coefficient of $J_i^0 \cdot \tau_i' \cdot D_i$ is not significant, however, and thus, the effects do not differ by educational background. These features of the initial status effect are consistent with those in the current state equation. Moreover, educational background and a junior high school score are not significant. These results are also similar to those from the current state equation.

Among the variables relating to the conditions at the time of finding the previous job, the coefficients of age and marital status present results similar to those in the case of the current state equation. On the contrary, the duration of non-employment shows the negative effect only for women. For men, an absence of work in one's career does not work disadvantageously for obtaining regular employment. The unemployment rate at the time of finding a job shows the negative effect on the probability of finding regular employment. This finding differs from the result in the current state equation, suggesting that if a worker repeats job changes, the labor market condition might become less important to the determination of his or her employment status, and the past employment status becomes more influential.

Let us turn to the results of the initial state equation (5). The estimates for male and female respondents are presented in Columns 3 and 6, respectively. Here, the estimated coefficients of the proxy variables for workers' abilities are significant for both genders in contrast to those in the other two equations. First, new graduates with a higher level of education have more opportunities of being employed as regular workers in their first jobs.[42] Second, the junior high school score is also an effective determinant of employment status. Although the estimated coefficients do not necessarily increase along with score levels and are not necessarily significant, we find a tendency that a new entrant with a middle or higher junior high school score can find a regular job more frequently.[43] This finding suggests that educational background or the junior high school score is effective only for the determination of the first employment status. While employers regard applicants' abilities as important when they select new graduates, they emphasize workers' past employment statuses rather than abilities when they recruit mid-career workers.

Age at the time of entry to the labor market reduces the probability of finding regular employment. The positive effect of education mitigates the negative effect of age. Marital status does not affect the probability of finding regular employment at the beginning of one's career for men, but it does reduce the probability for women.

Importantly, the unemployment rate at entry shows a negative impact. If workers happened to have entered the labor market in recessionary conditions and failed to engage in regular employment regardless of their abilities or preferences, this in turn assigns them a low probability of transiting from a non-regular to a regular position, as indicated by the result of the current state equation. Judging from the estimates in the current state equation, the effect of labor market conditions at entry decreases as external labor market experience rises for men, but the pace is slow.

Combining the results of the three equations highlights that the dependence of the current employment status on the initial employment status does not arise merely because the transition probability between non-regular and regular employment is low. Instead, the initial state differentiates the future transition probability even among homogeneous workers. In addition, at the time of entry, the possibility of finding a regular job is affected by the aggregate labor market conditions. Therefore, temporary business-cycle conditions may affect a certain generation's lifetime employment prospects, that is, cohort effects are present.

However, the conclusions drawn thus far have been stated qualitatively only. The estimated coefficients cannot reveal the quantitative impact, namely the size of the effect on the probability of finding regular employment. Moreover, the effect of a change in an explanatory variable on the transition probability differs among workers according to the values of the other variables. Thus, the size of those effects on the overall economy depends on the distribution of the values of the exogenous variables across workers. We

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[42]Male technical college graduates are an exception. The estimated coefficient of the dummy is insignificant with a large p-value. The large standard error may be due to the small number of relevant respondents.

[43]Most of the estimated coefficients of these dummies are significant at the 10% level.

take the average of the individual effects over the sample to evaluate an economy-wide first job effect quantitatively, as discussed in the next subsection.

Finally, the estimated correlation coefficients among the disturbances of the three equations are statistically insignificant, as shown in the bottom panel of Table 3. The correlation coefficients are denoted by ρ_{ij}, $i, j = 1, 2, 3$, where the numbers 1, 2, and 3 correspond to the initial, previous, and current state equations, respectively. The reported p-values and results of the likelihood ratio test show that the disturbances in the system are independent. If unobserved individual characteristics, which are thought to be the main source of the endogeneity of past employment statuses, are present, the disturbances should indicate positive correlations. However, we do not find such evidence in the results, perhaps because the explanatory variables related to individual abilities and conditions could have effectively absorbed the individual heterogeneity.

If J_i^0 and J_i' are both exogenous, as suggested by the above estimation results, then (9) can be estimated independently. Therefore, we also estimate a univariate probit model. (This corresponds to estimating the trivariate system under the constraints that the correlations among the disturbances are equal to zero.) Table 4 presents the estimation results for the univariate model (9), showing that the estimated coefficients and standard errors in the univariate probit case do not differ conspicuously from those in the trivariate case (Table 3). The most notable difference is that the coefficient of J_i^0 for men and women is smaller by a sizable amount in the univariate case than in the trivariate case. Nevertheless, the above arguments based on the trivariate estimation results are qualitatively unaltered. Moreover, the mean sizes of marginal effects, which are more important for interpreting the results, differ little between the trivariate and univariate cases, as shown in the next subsection.

7.2 Quantitative Impact of First Job Effects

In the previous subsection, we found evidence of cohort effects. However, the coefficients of the probit model do not represent the marginal effects of the variables on the probabilities. Thus, the coefficient estimates in Tables 3 and 4 do not offer quantitative implications about the transition probabilities. To evaluate the impact of cohort effects (equivalently first job effects in this case), we must thus compute the sample average of individual marginal effects as follows.

Consider for each worker i ($i = 1, \ldots, N$) the conditional probability of the current employment status being regular given the previous and initial employment statuses (as well as the values of the exogenous variables):

$$\Pr(J_i = 1 \mid J_i' = j, J_i^0 = k, G_i = g_i), \quad k, j = 0, 1. \tag{11}$$

We can compute this conditional probability for each combination of k and j, irrespective of his or her actual current, previous, and initial employment statuses. The marginal effect of a change in the initial employment status on the conditional probability of finding a regular current job is then given by

$$\Pr(J_i = 1 \mid J_i' = j, J_i^0 = 1, G_i = g_i) - \Pr(J_i = 1 \mid J_i' = j, J_i^0 = 0, G_i = g_i), \quad j = 0, 1.$$

This difference can also be regarded as the marginal effect of the initial employment status on the transition probability from the previous employment status j to the current employment status 1 for worker i with the values of the exogenous variables equal to g_i. Similarly, the marginal effect of the previous employment status on the conditional probability of finding a regular current job is given by

$$\Pr(J_i = 1 \mid J'_i = 1, J_i^0 = k, G_i = g_i) - \Pr(J_i = 1 \mid J'_i = 0, J_i^0 = k, G_i = g_i), \quad k = 0, 1.$$

If $k = 1$ ($k = 0$), this is the difference between the regular to regular transition probability and the non-regular to regular one for a worker whose initial employment status is regular (non-regular).

Note that the values g_i of the exogenous variables are different among workers as are the magnitudes of the individual marginal effects defined above. Therefore, we take the average of the individual marginal effects over the whole sample, which we call the average marginal effect (AME hereafter) of the initial employment status and the previous employment status. For example, the AME of the initial employment status on the conditional probability of the current job being regular is equal to

$$\frac{1}{N} \sum_{i=1}^{N} \left\{ \Pr(J_i = 1 \mid J'_i = j, J_i^0 = 1, G_i = g_i) - \Pr(J_i = 1 \mid J'_i = j, J_i^0 = 0, G_i = g_i) \right\}$$

$$= \overline{\Pr}(J = 1 \mid J' = j, J^0 = 1) - \overline{\Pr}(J = 1 \mid J' = j, J^0 = 0) \quad j = 0, 1, \tag{12}$$

where $\overline{\Pr}(J = 1 \mid J' = j, J^0 = k)$, $k, j = 0, 1$ denotes the sample average of the individual conditional probabilities (11). In the following discussions, we also refer to (12) as the AME of the initial employment status on the transition probability from a regular/non-regular previous job to a regular current job.

When the disturbances in the system (9), (10), and (5) are correlated, that is, J'_i and J_i^0 are endogenous, the conditional probability (11) depends on the correlations of the disturbances as well as the coefficients of the latent equations. (See the argument following equation (7).) We use the maximum likelihood estimates of these parameters to compute the conditional probabilities and hence the AMEs.

The estimated average conditional probabilities and AMEs are shown in Panel (A) of Table 5. The first column shows the results for men. Line 1 indicates that the probability of non-regular to regular transition is 0.460 on average for workers who started working as non-regular workers. Line 2 shows that this figure rises to 0.553 if they started as regular workers. Hence, the AME of the initial employment status on the non-regular to regular transition probability is 0.093 as shown in Line 5. Thus, the average probability for male workers who started their careers as regular employees to return to regular jobs even after becoming non-regular is higher by 0.093 than that for workers whose initial jobs were non-regular.

On the other hand, Lines 3 and 4 indicate that the average probability of regular to regular transition is 0.820 for male workers whose first employment status was non-regular and 0.854 for those who started working as regular employees. Thus, as shown

in Line 6, the AME of the initial employment status on the probability of staying in a regular job is 0.034. Male regular workers find other regular jobs at a probability greater than 0.8, irrespective of their initial employment statuses. We can thus conclude from Lines 5 and 6 that first job effects are small.

The figures in Lines 1–4 also suggest that serial state dependence is a dominant source of the persistence of employment status. Suppose that an individual entered the labor market as a non-regular worker. The probability that he or she finds another regular job is 0.820 (0.460) if his or her previous job was regular (non-regular). Thus, the AME of the previous employment status is 0.360 when the initial employment status was non-regular, as shown in Line 7. In the case where the initial employment status was regular, the probability of finding a regular current job is 0.854 (0.553) if he or she had a regular (non-regular) status in his or her previous job. Therefore, the AME of the previous job in this case is 0.301, as shown in Line 8. Thus, we can conclude that the probabilities of the regular to regular transition are larger than those of the non-regular to regular transition. This difference exceeds 0.3, regardless of the initial employment status. This is evidence of the dominance of serial state dependence.

The second column in Panel (A) displays the results for women. The transition probabilities from a non-regular job to a regular jobs reported in Lines 1 and 2 are much smaller than those for men, irrespective of the initial employment status. Line 2 suggests that even if female workers had regular jobs at first, a later transition from non-regular to regular jobs occurs at a probability of only 0.220. If they started their careers in non-regular employment, the probability falls to 0.166, as shown in Line 1. These figures suggest that female workers find it difficult to seek regular jobs despite repeated job changes once they have non-regular jobs. The AME of the initial employment status on the non-regular to regular transition probability is 0.054 (see Line 5). Lines 3 and 4 show the average probabilities of keeping a regular position during turnovers for female workers. These probabilities are also much lower, by over 0.3, than those for their male counterparts. The divergence of probabilities between Lines 3 and 4 is small, meaning that the AME of the initial employment status on the regular to regular transition probability is 0.055, as shown in Line 6.

The comparison of the AMEs of the previous employment status between men and women in Lines 7 and 8 shows that these figures are close. The dominance of serial state dependency is also found in the case of female workers. On the other hand, the comparison of figures in Lines 1–4 between genders reveals that all the probabilities of moving to a regular job are lower for women than for men. Even the regular to regular transition probabilities are around 0.5 in the case of female workers. We find it unusual for women to change to a regular job.

To summarize the results for both men and women, the AMEs of the initial employment status are not substantial in comparison with the average conditional probabilities of having a regular job. Instead, the difference in the previous status is more influential on the current status. We consequently conclude that first job effects are not quantitatively important and that serial state dependence plays a prior role in the persistence

of employment status.

As stated above, the correlations among the disturbances in (9), (10), and (5), that is, individual heterogeneity, were taken into account to compute the average conditional probabilities and AMEs reported in Panel (A) of Table 5. However, the estimated correlation coefficients are statistically insignificant for both men and women. These results imply that there is no individual heterogeneity and thus no spurious state dependence. Moreover, the estimated signs of correlation are negative in all cases except one case as described in Subsection 7.1. Individual heterogeneity stemming from abilities or preferences should induce positive correlations. Indeed, it is hard to find a specific example that can account for the negative correlations. To avoid the undesirable influence of the insignificantly estimated negative correlations, we also compute the conditional probabilities and AMEs based on the univariate probit model, as displayed in Table 4. This corresponds to the case in which the correlations among the disturbances are restricted to zero in the trivariate probit model. In other words, serial state dependence in the univariate case does not include spurious state dependence.

Since J_i' and J_i^0 in (1) are exogenous in this case, the individual conditional probabilities (11) of the regular current employment are simply given by (2), from which the average conditional probabilities and AMEs are calculated in the same way as before. Lines 13–18 in Panel (B) of Table 5 report the results. Each probability is close to the corresponding one in the trivariate case. Among them, the largest difference is observed for the AME of the initial employment status on the non-regular to regular transition for male workers. Line 17 indicates that first job effects cause a probability difference of 0.154 in the univariate case, while the difference is 0.093 in the trivariate case. However, they are smaller than the effects of serial state dependence. The AMEs in Lines 19 and 20 suggest that the probability of finding a regular job is about 0.3 to 0.4 higher when the previous job is regular than when it is non-regular.

Now, we should realize that the effects of the initial employment status on the current one may decline along with years of external experience since the probit estimations in both the trivariate and the univariate cases indicate negative coefficients of the cross term between the initial employment status and external experience (see Subsection 7.1 and Tables 3 and 4). To quantify the rate of this decrease, we calculate the influence of external experience on first job effects as follows.

Consider a counterfactual situation in which each respondent's years of external experience increase from τ_i to $\tau_i + t$, where τ_i is his or her actual external experience, and t represents a certain period of additional years. Recall that τ_i is defined as elapsed years from the year of entry to the year of obtaining the current job. Therefore, in reality τ_i does not change independent of the other explanatory variables related to the year of hiring or separation. However, we ignore such interactions in order to extract the pure effects of external experience. Since the AME of the initial employment status (12) depends on workers' external experience, we compare the AME with the actual τ_i and $\tau_i + t$, keeping the other variables unchanged. The difference represents the effect of an increase t in external experience on the AME of the initial employment status. That

is, the change in the AME due to additional t years of external experience is defined by

$$\frac{1}{N}\sum_{i=1}^{N}\left[\left\{\Pr(J_i = 1 \mid J_i' = j, J_i^0 = 1, T_i = \tau_i + t, H_i = h_i)\right.\right.$$
$$\left. - \Pr(J_i = 1 \mid J_i' = j, J_i^0 = 0, T_i = \tau_i + t, H_i = h_i)\right\}$$
$$ - \left\{\Pr(J_i = 1 \mid J_i' = j, J_i^0 = 1, T_i = \tau_i, H_i = h_i)\right.$$
$$\left.\left. - \Pr(J_i = 1 \mid J_i' = j, J_i^0 = 0, T_i = \tau_i, H_i = h_i)\right\}\right], \quad j = 0, 1,$$

where T_i indicates the years of external experience, H_i is a vector of the exogenous explanatory variables other than T_i, and h_i is its realized value.

Note that this should not be interpreted as a decrease in the first job effects t years after entry, since each respondent's years of experience are set to $\tau_i + t$ rather than t. This is a comparison of the AMEs of the initial employment status between workers with τ_i years of external experience and those with identical characteristics except that they have $\tau_i + t$ years of external experience.

The results are shown in Table 5 in Lines 9–12 for the trivariate case and Lines 21–24 for the univariate case. Since there is little difference in the estimated AMEs between the two cases, let us examine the univariate case. The changes in the AMEs of the initial employment status in the case of $t = 1$ are shown in Lines 21 and 22. The advantage of being a regular worker upon entry with respect to the non-regular to regular transition probability would decrease by 0.016 for men and by 0.006 for women if all workers were employed for an additional year in the labor market before obtaining their current job. The AME on the regular to regular transition probability would decline by 0.009 for men and by 0.007 for women.

The changes in the AMEs of the initial employment status in the case of $t = 10$ are shown in Lines 23 and 24. Although it may not be plausible to assume that workers with the same characteristics, except a nine-year gap in external experiences exist, we see that each of the changes in the AMEs at $t = 10$ is close to 10 times the size of its counterpart at $t = 1$. This finding suggests that the AMEs of the initial employment status decline almost linearly in t, which in turn implies that they would also decline linearly in τ_i. Therefore, the first job advantages with respect to the non-regular (regular) to regular transition probability decrease year-by-year by the amounts indicated in Line 21 (22). Thus, the changes in the AMEs of the initial employment status are judged to be small and thus the rate of decrease is low, as expected from the estimated coefficients in the probit model. However, the AMEs of the initial employment status are small per se, suggesting that most of the existing first job effects cease within 10 years.

Recall that the diminishing first job effects are not detected with statistical significance for women in both the trivariate and the univariate cases in the previous subsection. However, even if first job effects are permanently effective for women, the size of the effects is small from the beginning.

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To sum up, although first job effects, or cohort effects, exist, the quantitative influences on employment status are not that substantial, at least when we evaluate them under the actual distributions of the other characteristics across workers. On the other hand, serial state dependency matters more critically for labor market segmentation. Because the low transition probabilities from non-regular jobs bring about the dual structure in the labor market, we should examine the mechanism of the intertemporal dependence of employment status to investigate the source of polarization in the labor market.

Further, cohort effects are potentially at play and they may appear modestly under the distribution of individual workers' characteristics or circumstances at the present moment. If that is the case, the cohort effects might become tangible when situations change.

8   Conclusion

In this study, we examined the persistency of employment status over time against the background of the recent increase in the share of non-regular workers. The source of persistency can be attributed to two phenomena: first job effects and serial state dependence. As per the term "first job effects," a worker's employment status in a job at the time of entry into the labor market influences his/her future employment statuses for a long time, even permanently. On the other hand, serial state dependence means that the determination of a worker's employment statuses depends on employment statuses in his/her previous job.

The first job effects are confirmed empirically by observing the positive correlation between the first and the current employment status. However, such correlation can be found when only strong positive serial state dependence exists, since the initial status can affect the current one for a long time by repeating intertemporal dependence between two consecutive employment statuses. However, the two phenomena are quite different. The first job effect hypothesis emphasizes the special role of experiences or environments early on in one's career. On the other hand, serial state dependence occurs evenly at any stage of one's career, with no special role of the initial employment status.

We proposed an empirical method to distinguish these two phenomena and to evaluate the significance of each. Methodologically, we estimated a probit model where the current employment status is an explained variable, and both the initial and previous employment statuses are included in explanatory variables. We considered the endogenous bias arising from individual heterogeneities, which is called spurious state dependence. To manage endogenous nature, a recursive trivariate probit model that consisted of equations for the employment status in the current, previous, and first jobs, were constructed. This model was estimated by using the data of workers who changed their jobs just twice, taken from a micro survey on employment in Tokyo metropolitan area.

Consequently, we verified the presence of both serial state dependence and first job

effects on the persistence of employment status. Additionally, we found insignificant effects of individual heterogeneity on it. Moreover, by exploiting the multivariate structure, we also examined and detected cohort effects, which means that the temporary economic conditions at a worker's time of entry have a long-lasting influence on his or her lifetime working conditions.

To quantify the impact of first job effects and serial state dependence, we computed the average marginal effects. The results revealed that the quantitative impact of cohort effects on employment status is not that substantial. Furthermore, most existing cohort effects cease within 10 years. On the other hand, serial state dependence has greater influence on the persistency of employment statuses, and seems responsible for the rising labor market segmentation. These assertions apply to each gender, although we found that female workers tend to move into the non-regular sector more frequently than male workers. However, there is no difference by educational level. The findings presented in this paper suggest that we should pursue the mechanism of the intertemporal dependence of employment status to investigate the source of the polarization of the labor market.

Table 1: Employment Status Transition

	Men			
	High school graduate Sample size = 2,070 (474)		University graduate Sample size = 3,529 (819)	
	Current employment status			
	Non-Regular	Regular	Non-regular	Regular
Initial employment status				
Non-regular	0.51 (0.48)	0.49 (0.52)	0.42 (0.40)	0.58 (0.60)
Regular	0.27 (0.24)	0.73 (0.76)	0.19 (0.18)	0.81 (0.82)
Previous employment status				
Non-Regular	0.67 (0.60)	0.33 (0.40)	0.58 (0.53)	0.42 (0.47)
Regular	0.18 (0.16)	0.82 (0.84)	0.14 (0.13)	0.86 (0.87)
	Women			
	High school graduate Sample size = 3,988 (926)		University graduate Sample size = 2,213 (553)	
	Current employment status			
	Non-Regular	Regular	Non-regular	Regular
Initial employment status				
Non-regular	0.77 (0.75)	0.23 (0.25)	0.62 (0.61)	0.38 (0.39)
Regular	0.69 (0.69)	0.31 (0.31)	0.58 (0.60)	0.42 (0.40)
Previous employment status				
Non-regular	0.85 (0.84)	0.15 (0.16)	0.79 (0.78)	0.21 (0.22)
Regular	0.51 (0.48)	0.49 (0.52)	0.40 (0.37)	0.60 (0.63)

Notes:
Individuals who experienced no turnover are excluded from the sample. The initial job and the previous job are the same for those who changed jobs once. The numbers in parentheses are the proportions of transitions among individuals who changed jobs twice.

Table 2: Distribution of the Number of Job Changes

	Ratio			
	Men		Women	
	Initial employment status			
	Non-Regular	Regular	Non-regular	Regular
Sample size	1,431	9,675	1,667	6,689
Turnover number				
0	0.35	0.52	0.31	0.19
1	0.24	0.21	0.18	0.16
2	0.15	0.12	0.15	0.13
3	0.10	0.08	0.13	0.11
4	0.05	0.04	0.07	0.06
5	0.05	0.03	0.08	0.05
6 or more	0.06	0.03	0.07	0.07

Notes:
The proportion of individuals who experience turnover at the indicated number of times relative to the total of each category.

Table 3: Results of the Trivariate Probit Model

	Men			Women		
	1	2	3	4	5	6
	Current state equation (Third job)	Previous state equation (Second job)	Initial state equation (First job)	Current state equation (Third job)	Previous state equation (Second job)	Initial state equation (First job)
Initial employment: Regular (J^0)	1.609 (3.40) [0.001]	1.504 (3.70) [0.000]		1.125 (3.12) [0.002]	0.7176 (1.99) [0.047]	
× University graduate (D)	0.3033 (1.07) [0.286]	0.1452 (0.61) [0.541]		-0.08559 (-0.35) [0.729]	-0.1861 (-0.88) [0.381]	
× External experience up to the current job (τ)	-0.04716 (-3.60) [0.000]			-0.01696 (-1.51) [0.131]		
× University graduate (D) × External experience up to the current job (τ)	-0.004335 (-0.45) [0.656]			-0.01474 (-1.44) [0.150]		
× External experience up to the previous job (τ')		-0.03377 (-2.45) [0.014]			-0.01616 (-1.14) [0.253]	
× University graduate (D) × External experience up to the previous job (τ')		-0.008076 (-0.84) [0.399]			-0.002901 (-0.25) [0.799]	
Previous employment: Regular (J')	0.9677 (1.92) [0.055]			1.048 (3.51) [0.000]		
× University graduate (D)	-0.15881 (-0.77) [0.438]			-0.002556 (-0.02) [0.987]		
Age when finding the current job	-0.01494 (-1.37) [0.172]			-0.004872 (-0.49) [0.621]		
Age when finding the previous job		0.006101 (.0.49) [0.621]			0.01062 (0.82) [0.414]	
Age when finding the initial job			-0.09269 (-3.90) [0.000]			-0.07529 (-3.48) [0.001]

	(1)	(2)	(3)	(4)	(5)	(6)
Marital status when finding the current job	0.4403 (3.90) [0.000]			-0.7100 (-7.54) [0.000]		
Marital status when finding the previous job		0.4328 (3.70) [0.000]			-0.6037 (-7.10) [0.00]	
Marital status when finding the initial job			0.2207 (0.70) [0.484]			-0.7284 (-2.49) [0.013]
Interval between the previous job and the current job	-0.004331 (-2.45) [0.014]			-0.004780 (-5.20) [0.000]		
Interval between the initial job and the previous job		-0.0000225 (-0.02) [0.983]			-0.002717 (-2.87) [0.004]	
Unemployment rate when finding the current job	-0.04999 (-0.71) [0.475]			-0.07863 (-1.42) [0.155]		
Unemployment rate when finding the previous job		-0.2119 (-4.34) [0.000]			-0.1445 (-3.69) [0.00]	
Unemployment rate when finding the initial job			-0.3104 (-7.69) [0.000]			-0.3354 (-9.38) [0.000]
Educational background						
High school	-0.5510 (1.00) [0.316]	0.1667 (0.32) [0.749]	1.299 (2.29) [0.022]	-0.4939 (-0.98) [0.329]	-0.2015 (-0.39) [0.698]	1.912 (3.50) [0.000]
Vocational school	-0.5173 (-0.90) [0.367]	0.2620 (0.47) [0.637]	2.285 (3.93) [0.000]	-0.5392 (-1.05) [0.293]	-0.2796 (-0.53) [0.597]	2.182 (3.95) [0.000]
Junior college	-0.1201 (-0.17) [0.862]	0.1552 (0.24) [0.809]	2.117 (2.98) [0.003]	-0.6629 (-1.28) [0.201]	-0.2992 (-0.56) [0.576]	2.487 (4.49) [0.000]
Technical college	-0.4780 (-0.70) [0.484]	0.1892 (0.29) [0.773]	6.387 (0.05) [0.962]	-0.1592 (-0.25) [0.801]	0.1478 (0.23) [0.817]	1.651 (2.30) [0.021]
University	-0.4905 (-0.83) [0.409]	0.3904 (0.67) [0.503]	2.522 (4.34) [0.000]	-0.2813 (-0.54) [0.592]	-0.1801 (-0.33) [0.739]	2.464 (4.41) [0.000]
Graduate school	-0.1597 (-0.25) [0.801]	0.7135 (1.18) [0.239]	2.549 (4.02) [0.000]	-0.3840 (-0.70) [0.486]	0.2763 (0.49) [0.625]	2.024 (3.15) [0.002]
Junior high school score						
Upper	0.2560 (1.05) [0.295]	0.2380 (1.00) [0.316]	0.4267 (1.81) [0.071]	0.3586 (1.40) [0.162]	0.2633 (1.14) [0.255]	0.3378 (1.40) [0.161]
Upper-middle	0.02830	0.1088	0.4017	0.1085	0.1397	0.4583

	(1)	(2)	(3)	(4)	(5)	(6)
	(0.12) [0.906]	(0.46) [0.642]	(1.74) [0.083]	(0.43) [0.671]	(0.61) [0.544]	(1.93) [0.054]
Middle	0.2955 (1.24) [0.217]	0.2495 (1.08) [0.281]	0.5251 (2.31) [0.021]	0.1239 (0.49) [0.624]	0.05664 (0.25) [0.804]	0.4656 (1.99) [0.047]
Lower-middle	0.1102 (0.44) [0.661]	0.2303 (0.95) [0.343]	0.2051 (.0.84) [0.403]	0.1417 (0.53) [0.598]	-0.1050 (-0.43) [0.667]	0.2200 (0.87) [0.383]
Constant	0.2669 (0.41) [0.683]	-0.2073 (-0.34) [0.732]	1.507 (2.09) [0.036]	-0.2742 (-0.44) [0.662]	0.02866 (0.05) [0.962]	1.045 (1.53) [0.126]
Correlation coefficient between the residuals of						
the previous and the initial equations: ρ_{21}		-0.2478 (-1.02)[0.308]			-0.02050 (-0.11) [0.912]	
the current and the initial equations: ρ_{31}		-0.3596 (-1.62)[0.106]			-0.3214 (-1.67)[0.095]	
the current and the previous equations: ρ_{32}		0.1626 (0.59)[0.555]			-0.01658 (-0.09)[0.929]	
Likelihood-ratio test of $\rho_{21} = \rho_{21} = \rho_{32} = 0$		4.426 [0.2189]			2.51073 [0.4734]	
Number of observations		1,256			1,454	

Notes:
1. Numbers in parentheses are t-values. Numbers in square brackets are p-values.
2. The trivariate probit models were estimated by using the maximum simulated likelihood method. We used the `mvprobit` [Cappellari and Jenkins (2003)] command in Stata, where the number of pseudo-random variates drawn for simulating the likelihood was set to 500.

Table 4: Results of the Univariate Probit Model

	1 Men	2 Women
	Current state equation (Third job)	
Initial employment: Regular (J^0)	0.9737 (3.99) [0.000]	0.6282 (3.09) [0.002]
$\times$ University graduate (D)	0.2207 (0.76) [0.446]	-0.1124 (-0.44) [0.675]
$\times$ External experience up to the current job (τ)	-0.04638 (-3.52) [0.000]	-0.01722 (-1.52) [0.128]
$\times$ University graduate (D) $\times$ External experience up to the current job (τ)	-0.004165 (-0.42) [0.676]	-0.01405 (-1.35) [0.176]
Previous employment: Regular (J')	1.217 (7.68) [0.000]	1.039 (10.27) [0.000]
$\times$ University graduate (D)	-0.1516 (-0.72) [-0.470]	0.007530 (0.05) [0.963]
Age when the job started	-0.01362 (-1.23) [0.219]	-0.001675 (-0.17) [0.865]
Marital status when the job started	0.4325 (3.90) [0.000]	-0.7296 (-8.77) [0.000]
Interval between the job and the former job	-0.004715 (-2.70) [0.007]	-0.004693 (-5.64) [0.000]
Unemployment rate when the job started	-0.05750 (-0.81) [0.416]	-0.09155 (-1.65) [0.098]
Educational background High school	-0.3620 (-0.66) [0.508]	-0.2249 (-0.46) [0.645]
Vocational school	-0.2393 (-0.43) [0.667]	-0.2648 (-0.54) [0.592]
Junior college	0.1654 (0.24) [0.862]	-0.3573 (-0.72) [0.470]
Technical college	-0.1550 (-0.23) [0.815]	0.05525 (0.09) [0.930]
University	-0.1612 (-0.29) [0.774]	0.007839 (0.02) [0.988]
Graduate school	0.1172 (0.19) [0.848]	-0.1832 (-0.33) [0.738]
Junior high school score Upper	0.3301 (1.38) [0.168]	0.4200 (1.64) [0.100]
Upper-middle	0.1155 (0.49) [0.623]	0.1929 (0.76) [0.445]

Middle	0.3845	0.2074
	(1.66) [0.097]	(0.83) [0.408]
Lower-middle	0.1506	0.1928
	(0.60) [0.548]	(0.71) [0.475]
Constant	0.2851	-0.2681
	(0.43) [0.666]	(-0.43) [0.666]
Number of observations	1,256	1,454

Notes:
1. Numbers in parentheses are t-values. Numbers in square brackets are p-values.
2. The univariate probit models were estimated by Stata's `probit` command.

Table 5: Conditional Probabilities and AMEs

Panel (A)	Men	Women
	Trivariate probit	
Conditional probability		
Non-regular to regular transition		
1. $\overline{\Pr}(J = 1 \mid J' = 0, J^0 = 0)$	0.4601	0.1658
2. $\overline{\Pr}(J = 1 \mid J' = 0, J^0 = 1)$	0.5528	0.2201
Regular to regular transition		
3. $\overline{\Pr}(J = 1 \mid J' = 1, J^0 = 0)$	0.8197	0.4787
4. $\overline{\Pr}(J = 1 \mid J' = 1, J^0 = 1)$	0.8536	0.5341
AME of the initial employment status: $J^0 = 0 \to J^0 = 1$		
Non-regular to regular transition		
5. AME $(J' = 0)$: $(2) - (1)$	0.09273	0.05431
Regular to regular transition		
6. AME $(J' = 1)$: $(4) - (3)$	0.03389	0.05541
AME of the previous employment status: $J' = 0 \to J' = 1$		
Initial employment status: non-regular		
7. AME $(J^0 = 0)$: $(3) - (1)$	0.3596	0.3129
Initial employment status: regular		
8. AME $(J^0 = 1)$: $(4) - (2)$	0.3007	0.3140
Change in the AME of the initial employment status		
9. After 1 year $(J' = 0)$	-0.01661	-.005820
10. After 1 year $(J' = 1)$	-0.009243	-.007390
11. After 10 years $(J' = 0)$	-0.1678	-.05420
12. After 10 years $(J' = 1)$	-0.1108	-.07461
Panel (B)	Men	Women
	Univariate probit	
Conditional probability		
Non-regular to regular transition		
13. $\overline{\Pr}(J = 1 \mid J' = 0, J^0 = 0)$	0.4087	0.1531
14. $\overline{\Pr}(J = 1 \mid J' = 0, J^0 = 1)$	0.5630	0.2210
Regular to regular transition		
15. $\overline{\Pr}(J = 1 \mid J' = 1, J^0 = 0)$	0.7997	0.4543
16. $\overline{\Pr}(J = 1 \mid J' = 1, J^0 = 1)$	0.8539	0.5378
AME of the initial employment status: $J^0 = 0 \to J^0 = 1$		
Non-regular to regular transition		
17. AME $(J' = 0)$: $(14) - (13)$	0.1543	0.06787
	(3.41) [0.001]	(2.90) [0.004]
Regular to regular transition		
18. AME $(J' = 1)$: $(16) - (15)$	0.05420	0.08333
	(1.63) [0.103]	(2.18) [0.029]

AME of the previous employment status: $J' = 0 \rightarrow J' = 1$

Initial employment status: non-regular

19. AME ($J^0 = 0$): (15) $-$ (13)	0.3910	0.3012
	(10.83) [0.000]	(10.63) [0.000]

Initial employment status: regular

20. AME ($J^0 = 1$): (16) $-$ (14)	0.2909	0.3166
	(9.20) [0.000]	(13.45) [0.000]

Change in the AME of the initial employment status

|		
21. After 1 year ($J' = 0$)	-0.01585	-.005707
	(-4.43) [0.000]	(-2.15) [0.032]
22. After 1 year ($J' = 1$)	-0.008853	-.007265
	(-4.25) [0.000]	(-2.10) [0.036]
23. After 10 years ($J' = 0$)	-0.1609	-.05324
	(-4.46) [0.000]	(-2.30) [0.022]
24. After 10 years ($J' = 1$)	-0.1054	-.07334
	(-3.73) [0.000]	(-2.11) [0.035]

Notes:

1. Numbers in parentheses are t-values. Numbers in square brackets are p-values.

2. In Panel (A), we used Stata programs `mdraws` and `mvnp` [Cappellari and Jenkins (2006)] to simulate the multivariate normal probabilities required for the computation of the conditional probabilities and marginal effects. The number of *draws* option given to the `mdraws` command was 500. See also the Appendix to this paper. In Panel (B), Stata built-in commands and functions were used for the computation of the conditional probabilities and marginal effects.

We do not provide t-values for the estimated AMEs in Panel (A) because it is difficult to calculate the standard errors by using the delta method, which was used to calculate the t-values in Panel (B).

Figure 1: Increases in non-regular employment in Japan
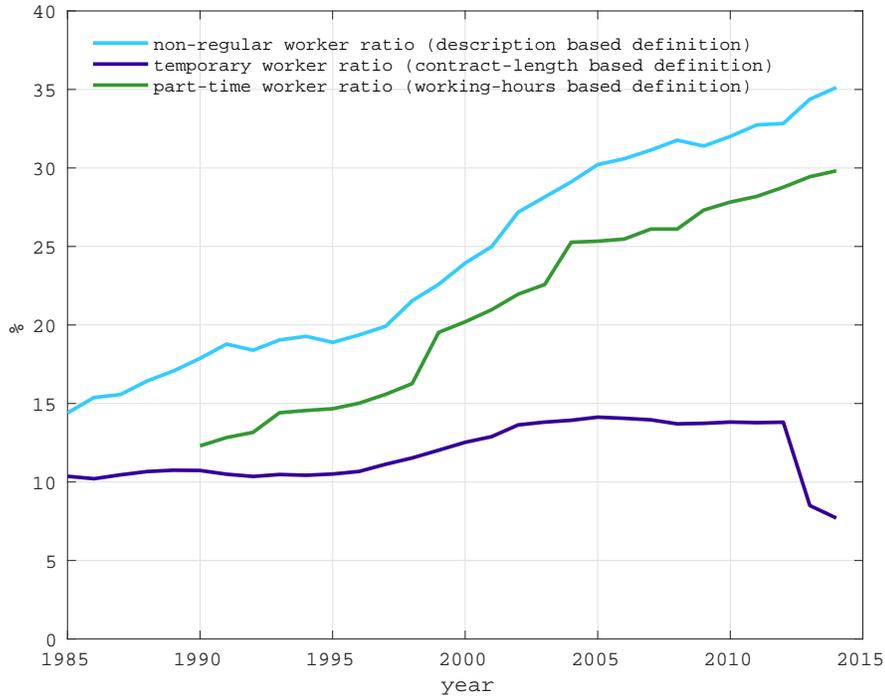
The non-regular worker ratio represents the proportion of non-regular employees to total employees. The figures are taken from the Labour Force Survey (Ministry of Internal Affairs and Communications). Non-regular employees are classified according to how workers are called in their workplaces. Six categories, namely "part-time worker," "temporary worker," "dispatched worker from temporary labour agency," "contract employee," "entrusted employee," and "other" are classified into non-regular employees. The remaining categories are "regular employee" and "executive of the company or corporation."

The temporary worker ratio represents the proportion of temporary and daily employees to total employees taken from the Labour Force Survey. Temporary employees are defined as "persons who work on a contract of a month or more but not more than a year" and daily employees are defined as "persons who work on a daily basis or on a contract of less than a month." Others are classified as long-term employees. The sharp decline in the temporary worker ratio in 2013 was driven by the change in the classification of long-term employees in the survey. The survey has differentiated between indefinite-duration contracts and limited-duration contracts since 2013. People who selected "temporary employee" as their employment status are thought to select long-term employees with limited-duration contracts.

The part-time worker ratio represents the proportion of part-time workers to total regular employees in establishments with more than four regular employees, where regular employees are defined as workers hired for an indefinite period or for longer than one month, or hired by the day or for less than one month and who were hired for 18 days or more in each of the two preceding months. (This definition of regular employees differs from the definition used in the text.) Figures are based on the Monthly

Labour Survey (Ministry of Health, Labour and Welfare). Part-time workers have shorter scheduled working hours per day/working hours per week than ordinary workers.

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Appendix

Let $G_i = (X_i^\top, Y_i^\top, Z_i^\top)^\top$ and g_i be its realized value. To compute the likelihood function of the system (1), (4), and (5), we need the probabilities (conditional on the exogenous variables):

$$\Pr\{J_i = j_i, J_i' = j_i', J_i^0 = j_i^0 \,|\, G_i = g_i\} \quad i = 1, \ldots, N, \tag{A.1}$$

where $j_i = 0, 1$, $j_i' = 0, 1$, $j_i^0 = 0, 1$.

Suppose, for instance, that $j_i = 1$, $j_i' = 1$, and $j_i^0 = 1$. By using the basic property of conditional probabilities, we have

$$\Pr\{J_i = 1, J_i' = 1, J_i^0 = 1 \,|\, G_i = g_i\}$$
$$= \Pr\{J_i = 1 \,|\, J_i' = 1, J_i^0 = 1, G_i = g_i\} \Pr\{J_i' = 1, J_i^0 = 1 \,|\, G_i = g_i\}. \tag{A.2}$$

From (1), the first conditional probability on the right-hand side can be rewritten as

$$\Pr\{J_i = 1 \,|\, J_i' = 1, J_i^0 = 1, G_i = g_i\} = \Pr\{u_i > -\alpha_1 J_i^0 - \beta_1 J_i' - \gamma_1^\top X_i \,|\, J_i' = 1, J_i^0 = 1, G_i = g_i\}$$
$$= \Pr\{u_i > -\alpha_1 - \beta_1 - \gamma_1^\top x_i \,|\, J_i' = 1, J_i^0 = 1, G_i = g_i\}.$$

Hence, (A.2) equals

$$\Pr\{u_i > -\alpha_1 - \beta_1 - \gamma_1^\top x_i \,|\, J_i' = 1, J_i^0 = 1, G_i = g_i\} \Pr\{J_i' = 1, J_i^0 = 1 \,|\, G_i = g_i\}$$
$$= \Pr\{u_i > -\alpha_1 - \beta_1 - \gamma_1^\top x_i, J_i' = 1, J_i^0 = 1 \,|\, G_i = g_i\}. \tag{A.3}$$

Applying the same conditioning argument to the last probability gives

$$
\begin{aligned}
\text{(A.3)} =&\Pr\{u_i > -\alpha_1 - \beta_1 - \gamma_1^\top x_i,\ J_i' = 1 \,|\, J_i^0 = 1, G_i = g_i\}\Pr\{J_i^0 = 1 \,|\, G_i = g_i\}\\
=&\Pr\{u_i > -\alpha_1 - \beta_1 - \gamma_1^\top x_i,\ v_i > -\alpha_2 - \gamma_2^\top y_i \,|\, J_i^0 = 1, G_i = g_i\}\Pr\{J_i^0 = 1 \,|\, G_i = g_i\}\\
=&\Pr\{u_i > -\alpha_1 - \beta_1 - \gamma_1^\top x_i,\ v_i > -\alpha_2 - \gamma_2^\top y_i,\ J_i^0 = 1 \,|\, G_i = g_i\}\\
=&\Pr\{u_i > -\alpha_1 - \beta_1 - \gamma_1^\top x_i,\ v_i > -\alpha_2 - \gamma_2^\top y_i,\ w_i > -\gamma_3^\top z_i \,|\, G_i = g_i\},
\end{aligned}
$$

where the second and fourth equalities follow from (4) and (5), respectively. Thus, since G_i is assumed to be exogenous, we have under the joint normality of the disturbances (u_i, v_i, w_i)

$$
\begin{aligned}
&\Pr\{J_i = 1, J_i' = 1, J_i^0 = 1 \,|\, G_i = g_i\}\\
=&\Pr\{u_i > -\alpha_1 - \beta_1 - \gamma_1^\top x_i,\ v_i > -\alpha_2 - \gamma_2^\top y_i,\ w_i > -\gamma_3^\top z_i \,|\, G_i = g_i\}\\
=&\int_{-\alpha_1-\beta_1-\gamma_1^\top x_i}^{\infty} \int_{-\alpha_2-\gamma_2^\top y_i}^{\infty} \int_{-\gamma_3^\top z_i}^{\infty} \phi_3(u, v, w)\, du\, dv\, dw,
\end{aligned} \tag{A.4}
$$

where ϕ_3 is the trivariate normal density function with mean $(0, 0, 0)$ and covariance matrix Σ. (Due to normalization, the diagonal elements of Σ are assumed to be unity.)

The probabilities (A.1) in which j_i, j_i', and j_i^0 take other values can be computed in a similar manner. Summing the log of these probabilities for all individuals gives the (conditional) log-likelihood function required for the maximum likelihood estimation of our model. Observe that (A.4) [or (A.1) in general] is the probability we obtain if all the explanatory variables in (1), (4), and (5) are treated as exogenous. This fact implies that we may compute the likelihood function ignoring the fact that the right-hand sides of (1), (4), and (5) involve endogenous variables. Therefore, we can utilize any computer program written for standard multivariate probit models (i.e., probit models with only exogenous explanatory variables) to estimate the system (1), (4), and (5).

For bivariate probit models, authors of some econometrics textbooks, such as Greene (2011) and Wooldridge (2010), point out the fact mentioned in the last paragraph. This result stems from the recursive structure of the model, and as seen from our exposition in this Appendix, the argument can be extended to recursive models with three or more endogenous variables. (Note also that the normality of the disturbances does not play an important role.)

In Section 7.2, we need to compute the conditional probability

$$
\Pr\{J_i = j_i \,|\, J_i' = j_i', J_i^0 = j_i^0 G_i = g_i\} = \frac{\Pr\{J_i = j_i, J_i' = j_i', J_i^0 = j_i^0 \,|\, G_i = g_i\}}{\Pr\{J_i' = j_i', J_i^0 = j_i^0 \,|\, G_i = g_i\}}.
$$

The denominator on the right-hand side can be calculated in a way analogous to (A.4). For example, if $j_i' = 0$ and $j_i^0 = 0$, we have

$$
\Pr\{J_i' = 0, J_i^0 = 0 \,|\, G_i = g_i\} = \int_{-\infty}^{-\alpha_2-\gamma_2^\top y_i} \int_{-\infty}^{-\gamma_3^\top z_i} \phi_2(v, w)\, dv\, dw,
$$

where ϕ_2 is the bivariate normal density function with mean $(0, 0)$ and a covariance matrix that is the 2×2 lower-right submatrix of Σ given above.